MULTIFRAME ESTIMATION OF CONTOUR EVOLUTION IN MEDICAL IMAGES

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ABSTRACT

A framework for temporal estimation of contour deformation in image sequences has been developed. The proposed solution for point-wise tracking finds, for a point, one optimum trajectory across multiple frames, in contrast with frame-to-frame tracking (2-frame). The multiframe approach aims (i) to find the complete point trajectory as the global optimal track over the space with multiple contours, and not as optimal sub-tracks concatenated over this set of contours; and (ii) take into account information from an extended time interval. The multiframe solution is framed as a shortest-path problem and uses the Dijkstra's algorithm. The method applies the dynamic programming technique to find the global trajectory. The algorithm requires no special initialization or markers. It is a non-invasive method and image modality independent. The usefulness of the multiframe tracking is illustrated using synthetic images. The method demonstrated to be consistent with methods published in the literature.

Index Terms— Left ventricular motion estimation, point-wise tracking, medical imaging, multiframe, shortest-path algorithm

1. INTRODUCTION

The detection and description of motion is one of the fundamental tasks of early vision. Motion estimation from image sequences has numerous applications in imaging sciences. In general, it consists of a correspondence problem that finds the positions of the object points at consecutive image frames through time. Usually, a tracking algorithm finds as output a set of tracks, where each track corresponds to the trajectory of a point between two frames. For image sequences, tracks are concatenated into a single trajectory.

The proposed method is to be applicable to estimation of the temporal evolution of the left ventricle (LV) in cardiac images. The tracking of heart wall can provide information such as effective movement and contraction of cardiac muscles. It is useful to assessment the ventricular function and changes in response to therapy; for analysis of

shape variation between normal and pathological structures; and to understand the evolution of diseases. Pathologies as ischemia modify the kinetics of the left ventricle of the heart: regions with necrosis do not deform; contractility decreases in ischemic regions; and do promote compensation phenomena of motion in normal regions to preserve the global myocardial function. Major developments in the past decade in medical image acquisition techniques have extended the capacity and fidelity of image-based diagnosis through different image acquisition modalities, e.g., Positron Emission Tomography (PET), Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) [1, 2].

To address the tracking of the LV in medical images, a variety of methods has been developed. These methods from model-based approaches for contour representation and motion estimation [3], to the use of markers moving along with cardiac muscle [4]. Geiger et al. [5] investigated the use of dynamic programming with search restrictions to get the mapping of bi-dimensional closed contours. Cohen and Herlin [6] proposed the use of geodesic paths applied to distance transforms of the given contours. The paths were achieved by following the opposite direction of the gradient of the distance transform sum. Papademetris et al. [7] proposed Bayesian optimization for the tracking in Echocardiography. They used "a priori" model of the muscle fibers for the orientation of tracking and a noise model based on curvature similarity. MR tagging is an important technique for tracking, however it applies only for Magnetic Resonance Images [8], it presents high costs and is difficult to use in clinic routine. McEachen et al. [9] proposed a cardiac wall tracking based on multiframe approach. Their method differs from the proposed at this work in several aspects: the representation scheme is based on deformable model, it uses harmonic to represent periodicity and incorporates a priori knowledge about heart wall motion, i.e., about the periodicity of the motion; the optimization is performed by means of an recursive least squares algorithm; and uses a velocity map for estimate initial correspondences.

The multiframe approach in this work aims (i) to find the complete point trajectory as the global optimal track over the space with multiple contours, and not as optimal sub-tracks concatenated over the set of contours; and (ii) take into account information from an extended time interval. The multiframe solution is framed as a shortest-path problem and uses a modified Dijkstra's algorithm [10, 11].

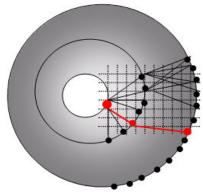


Fig. 1. Sequence of contours to be tracked on a graph. The pixels on the contours represent the nodes of the graph and the arcs connect elements of different contours. Arcs on larger nodes represent the optimum cost path.

In Section II, we present the multiframe tracking method. In Section III, we present the results of a comparison between multiframe tracking and Geiger's tracking [5]. Finally, we state our concluding remarks in Section IV.

2. MULTIFRAME TRACKING

2.1. Our approach

The multiframe tracking optimizes a cost function over multiple frames, in contrast with frame-to-frame tracking (2frame). The hypothesis is that a multiframe solution is adequate to produce precise and coherent results since the complete trajectory for a point is not a composition of piecewise optimal sub-tracks, as in 2-frame approach. The global optimal track for a point is achieved over a space with l contours. The path starts at a reference point $p_{\scriptscriptstyle u}$ on the C_t contour at time t, $1 \le t \le l$, and arrives the corresponding point p'_{v} at last contour C_{l-1} (Figure 1 and Figure 4). Along the path, the positions of the respective correspondences on all contours from C_t to C_{l-1} are stored. The multiframe approach differs from frame-to-frame one since the costs at a given time are estimated and stored using costs from previous frames, and propagates the estimated costs to next frames.

The tracking problem is reduced to a search problem in graph. We assume that the reader is familiar with the basic graph theory terminology. A graph G = (V, E) is a set of

vertices (V) and another of arcs (E) that connect the vertices. We associate the sequence of contours to be tracked with a graph in which the pixels on the contours represent the nodes of the graph and the arcs connect elements of different contours (Fig. 1).

2.2. Distance-based measure estimation

The closeness measure is the distance between the candidate point and the central point p_0 of a window search $W(C_i)$. This term penalizes the mapping of points with large distance from central point. The measure brings advantage for the closest candidate points to central point (Fig.2).

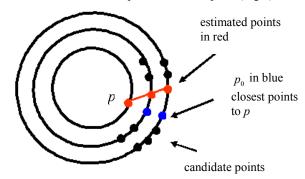


Fig. 2. Candidate points that composes the search window (black dots), and estimated points (red dots).

2.3. Curvature-based measure estimation

This measure in function cost estimates the curvature at each contour point. In bi-dimensional case, the curvature is based on direction changes at that point and can be obtained as cosine of half's angle between two successive vectors:

$$k(u) \equiv \cos(\theta/2) = \left| \mathbf{u}_1 - \mathbf{u}_2 \right| / 2, \tag{1}$$

where $\mathbf{u_1}$ and $\mathbf{u_2}$ are unit vectors of adjacent edges that intersect p_u (Fig. 3).

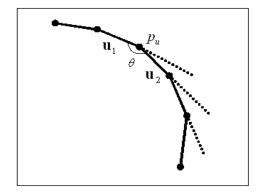


Fig. 3. Curvature measure estimation on contour points.

Track T_u : shortest-path from p_u to p'_v found through predecessors pointers

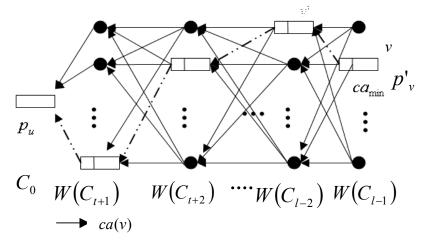


Fig. 4. Minimum cost path computation. Trajectory of the seed point p_u shown in doted lines. ca(v) is the cumulative cost along the paths.

2.4. Cost assignment

The cost function works directly on the contour data. To each reference point, closeness and similarity are taken into account. For estimate the cost between two possible matching points p_u and p_v , reference and candidate points, respectively, we have:

$$c(v) = w_1 |p_v - p_0| + w_2 |k(u) - k(v)| + c(v'), \qquad (2)$$

where k(u) and k(v) are the curvatures at the points, w_1 and w_2 are weights and c(v') is the cost of the possible correspondent of p_v at the previous contour. The mapping for a salient point is achieved by the total cost minimization over all contours

$$\min_{M} \left(\sum_{t=1}^{l} c(v) \right), \tag{3}$$

where M is the mapping between p_u and p_v (Fig.4).

2.5. Optimal Path Selection

The algorithm performs a single time over the search space represented by the graph with the contour sequence, in contrast with frame-to-frame approaches, for which the number of executions depends on the number of frames. The optimal configuration can be achieved by Dijkstra's algorithm [10], minimizing the total cost at Eq. 3.

Algorithm Multiframe Tracking

- begin
- given the n >= 3 contours C_t
- 3 construct a single graph from contours
- 4 compute the costs for the arcs using the weights, closeness and curvature features (Eq. 2)
- for complete contour sequence, find out the global optimum mapping for each seed point through dijkstra algorithm.
- 6 end

3. EXPERIMENTAL RESULTS

The input to the algorithm is a set of contours and the output is a set of trajectories. In the present method is assumed that: (i) the contours are previously segmented and extracted at each frame; (ii) the contours do not intersect during movement; and (iii) the temporal sampling of the images is sufficient for the contours have approximately the same length and shape between two frames. This is a reasonable assumption, as suggested by Friboulet *et al.* [12]. They observed the movement of salient points on LV and concluded that cardiac wall keep its curvature feature stable as a result of small muscle deformation along the cardiac cycle.

For simulated deformation, since we know the correct mapping, the mean Euclidean distance error was estimated. In order to evaluate and compare the proposed approach, several evolving contours were simulated and the tracking was performed using Geiger's [5] and Multiframe algorithm.

An initial contour *S* was generated as a regular polygon with 12 nodes in an image of size 256 x256 pixels. Several random contours were generated as follow: regular expansion of *S* with different velocities in pixels/unit. Table1 shows the average and standard deviation of Euclidean distance error for position tracking on simulations. The proposed approach presented better results compared to the Geiger's technique. In addition the proposed solution is simpler and uses a single cost function for multiple contours. The Fig. 5 depicts the results based on Multiframe tracking for 4 contours with 12 nodes.

Table 1. Average and standard deviation for mismatches (mean square error in pixels) for tracking using Geiger's and multiframe tracking approaches on 10 random sets with 20 contour sequences (Statistical validation with Test-t (Student), p = 0.05)). Each sequence is composed by 4 contours.

| | Geiger's Method | Multiframe Tracking |
|-----------------------|-----------------|---------------------|
| Average | 1.070 | 0.974 |
| Standard Deviation | 0.836 | 0.968 |

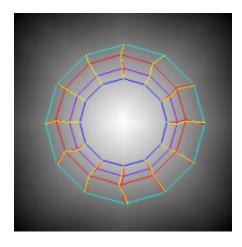


Fig. 5. Results of Multiframe Tracking. Yellow lines indicate the resultant matching.

4. CONCLUSIONS

We have presented an alternative approach to point-wise tracking called multiframe tracking. The method casts the tracking problem as a shortest-path one on graph. The proposed framework can be used for a large variety of motion models and cost functions, including statistical based functions. Based on experiments using synthetic data in 10 random sets with 20 contour sequences, we have shown a robust and simple methodology. The method does not

assume the presence of markers and is modality image independent. Although most methods in literature provides only sparse correspondence information, the work proposed do allow an optimum tracking for all points on the contour, not only markers or salient points. In addition, the optimization procedure is simple and coherent with the human perception process, which postpone inferences about motion until incoming information be sufficient.

5. REFERENCES

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